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Predicting Temperature in Orthopaedic Drilling using Back Propagation Neural Network

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Abstract

Present work deals with the prediction of temperature in orthopaedic drilling using back propagation neural network. Drilling of bone is common to prepare an implant site during orthopaedic surgery. The increase in temperature during such a procedure increases the chances of thermal invasion of bone which can cause thermal osteonecrosis. Drilling operations have been performed in polymethylmethacrylate (PMMA) (as a substitute for bone) work-piece by high- speed steel (HSS) drill bits over a wide range of cutting conditions. Drill diameter, feed rate and spindle speed are used as input for the back propagation neural network whereas temperature is taken as output. The performance of the trained neural network has been tested with the experimental results. Good agreement is observed between the predictive model values and experimental values.

Keywords: Orthopaedic drilling; Neural network; Osteonecrosis.

1. Introduction

Drilling of bone is one of the most important operation extensively used to prepare an implant site during orthopaedic surgery. During drilling, increase in bone temperature above a threshold can result in permanent or temproary loss of blood supply to the bones. In the absence of blood supply, the bone tissue dies and causes the bone to collapse, termed as thermal osteonecrosis [1-3]. There is no consensus among the researchers on the exact threshold temperature for the death of the human bone. However, majority of the authors believe an average temperature of 47°C for 1 min as threshold, above which the thermal osteonecrosis of humans will take place [1, 4-7]. Osteonecrosis reduces the stability of the fixation due to the rapid bone absorption in the necrotic region [8], also the presence of the necrotic tissue delays the healing of the fractured bone. Therefore, drilling of bone with minimum temperature is a major challenge for orthopaedic fracture treatment.

In recent years, the researchers have successfully employed the artificial intelligence tools for modeling and online monitoring of the manufacturing process [9-11]. In comparison to the other artificial intelligence tools neural network is easier to develop and requires less hardware and software resources. Also, it can effectively deal with systems that are very complex and cannot be modeled precisely even with various assumptions and approximations [12]. Neural network can be readily applied to the processes such as bone drilling as they provides effective and flexible means to deal with the nonlinearity associated with the practical decision-making.

2. Back propagation neural network

A Back Propagation Neural Network (BPNN) with generalised delta rule algorithm is used in our proposed model. Basic structure of back propagation neural network having input, hidden and output layers is shown in Fig. 1. Input layer receives a set of inputs or stimuli from the external sources and distributes the signals to the processing layer (also known as hidden layer because it has no external connections). Output layer receives processed information from the network, and sends the results out to an external receptor. The number of hidden layers and the number of nodes in a hidden layer is a variable quantity which depends upon the convergence criteria of results [9].

The figure 1 shows the l-m-n (l input neurons, m hidden neurons, and n output neurons) architecture of a back

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propagation neural network model. The input signals are modified by interconnection weights, known as weight vectors, V_{ij}, which represents the interconnection weights of i^{th} node of the first layer to j^{th} node of the second layer. The summation of the modified signal is again modified by a sigmoid transfer function (TF). Similarly the output signal from the hidden layer is modified by the interconnection weights (W_{ij}) of j^{th} node of hidden layer to k^{th} node of output layer. Again the sum of the modified signals is then modified by the sigmoid transfer function (TF) which gives the signal to the output layer.

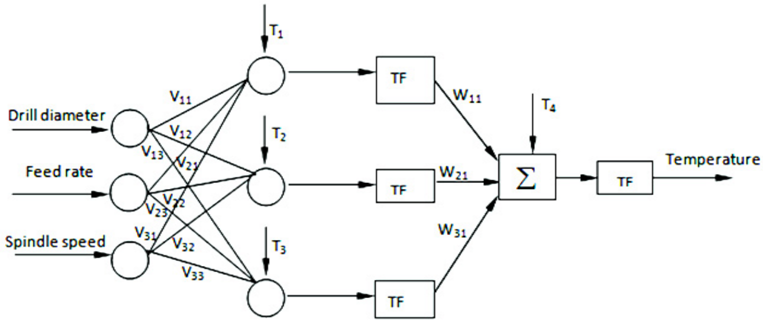

Fig. 1. Structure of the three-input-one-output BPNN unit.

Let $I_P = (I_{P1}, I_{P2,} I_{P3} ....I_{Pl}), P = 1,2,3...........N$ be the Pth pattern among N input patterns.

Output from a neuron in the input layer is,

$$O_{pi} = I_{pi}, i = 1,2,3......l \qquad (1)$$

Output from a neuron in the hidden layer is,

$$O_{pj} = f(\sum_{i=0}^{l} V_{ij} O_{pi}), j = 1,2.....m \qquad (2)$$

Output from a neuron in the output layer is,

$$O_{pk} = f(\sum_{j=0}^{m} W_{jk} O_{pj}), k = 1,2.......n \qquad (3)$$

f is a bounded, monotonic, non-decreasing, S-shaped function called as Sigmoid transfer function that provides a graded nonlinear response. It includes the logistic sigmoid function.

$$f(x) = \frac{1}{1 + e^{-x}}$$

Supervised learning of batch mode type is used in the present work for the training of BPNN. The training of the artificial neural network by back propagation involves three stages [12]: The feed forward of the input training pattern, the calculation and the back propagation of the associated error and the adjustment of the interconnecting weights. During training, the predicted output is compared with the desired output, and the mean square error is calculated. If the mean square error goes beyond a prescribed limiting value, it is back propagated from output to input, and weights are further modified using delta rule algorithm until the error or number of iterations is within the prescribed range.

Mean square error, E_p for pattern P is defined as

$$E_p = \sum_{i=1}^{n} \frac{1}{2} (D_{pk} - O_{pk})^2 \qquad (4)$$

Where D_{pk} is the target output and O_{pk} is the computed output for the i^{th} pattern.

Weight change at any time t, is given by

$$\Delta V(t) = -\eta E_p(t) + \alpha \Delta V(t-1) \qquad (5)$$

$$\Delta W(t) = -\eta E_p(t) + \alpha \Delta W(t-1) \qquad (6)$$

η = learning rate and $0 < \eta < 1$

α = momentum coefficient and $0 < \alpha < 1$

3. Experimental details

3.1. Material

The work material used is Polymethylmethacrylate (PMMA). Human bones are not easily available also it varies widely in density, cortical thickness and other parameters of interest. A more uniform and consistent material was desirable having properties similar to bone, allowing the results to be extrapolated for real surgical processes. PMMA has the properties comparable to the bone and is an acceptable surrogate for bone in such studies [13].The properties of bone and PMMA are shown in the Table 1.

Table 1.Comparision of properties for bone and PMMA

PROPERTIES	BONE	PMMA
Thermal conductivity (W/mK)	0.1-0.35	0.15-0.4
Specific heat (J/KgK)	1300	1400
Thermal diffusivity (m^2/Sec)	0.3*10-6	0.11*10-6
Density (Kg/m^3)	1800	1400

Specimens were made by using PMMA block of size 12cm x 7.5cm x 2cm. A hole of 1mm diameter is made at a depth of 5 mm to accommodate a thermocouple 0.7mm from the edge of test drill hole [14] (shown in figure. 2(b)).

3.2. Experimental set up

The experiments were conducted using the 3 axis MTAB Flex mill. X axis 250mm, Y axis 150mm, and Z axis 200mm. The table size is 420 × 180 mm. An Omega K- type thermocouple was used for temperature sensing. NI-DAQ 9219 was used with LABVIEW Software for the acquisition of the data. The experimental set up is shown in the figure 2.

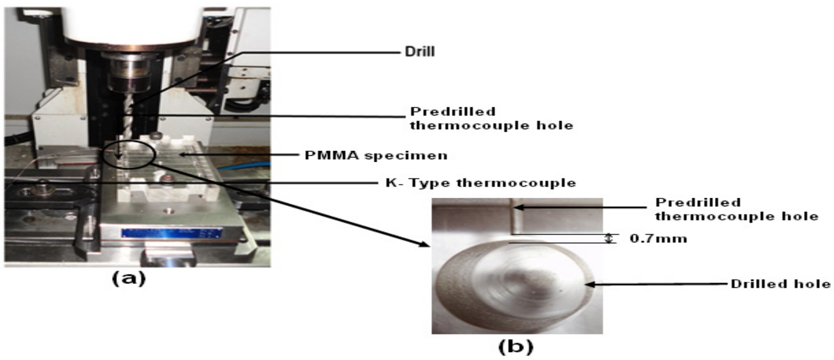

Fig. 2. (a) Experimental set up and (b) enlarged view of the predrilled thermocouple hole and drilled hole.

The drilling experiments are planned and carried out using L_{27} experimental design of orthogonal arrays. The drill bits used in the investigations are having diameter 6mm, 8mm, and 10mm. All tests were run without coolant at spindle speeds of 1500rpm, 2000rpm, and 2500 rpm, and feed rates of 35mm/min, 40mm/min, and 45mm/min. The parameters used and their levels are shown in Table 2. The parameters were chosen according to the data widely reported in literature for bone drilling [15-16]. The combination of cutting parameters for experiment along with the obtained temperature results is shown in the Table 3.

Table 2. Factors and levels considered for drilling.

	Control Factor	Level 1	Level 2	Level 3
A	Drill Diameter (mm)	6	8	10
B	Feed Rate (mm/min)	35	40	45
C	Spindle Speed (rpm)	1500	2000	2500

Table 3. Experimental conditions and result.

Experiment No.	Actual value			Temperature (°C)
	A	B	C	
1	6	35	1500	41.3391
2	6	35	2000	46.7783
3	6	35	2500	48.0000
4	6	40	1500	45.1756
5	6	40	2000	45.0246
6	6	40	2500	51.3897
7	6	45	1500	46.7180
8	6	45	2000	50.5785
9	6	45	2500	51.1552
10	8	35	1500	46.3431
11	8	35	2000	50.5280
12	8	35	2500	49.7903
13	8	40	1500	44.5953
14	8	40	2000	46.1804
15	8	40	2500	47.1815
16	8	45	1500	46.1920
17	8	45	2000	48.6203
18	8	45	2500	51.4934
19	10	35	1500	53.7469
20	10	35	2000	55.8367
21	10	35	2500	54.7636
22	10	40	1500	50.1228
23	10	40	2000	57.1087
24	10	40	2500	56.8153
25	10	45	1500	49.1733
26	10	45	2000	51.1272
27	10	45	2500	55.9826

4. Temperature prediction by BPNN

The entire data set obtained from the experiments is divided into18 training and 9 testing sets randomly. Normalized data sets were used for training and testing of the network. The data sets were normalized in the range of 0.1 to 0.9 using the following equation:

$$Y = 0.1 + 0.8\left(\frac{x - x_{max}}{x_{max} - x_{min}}\right)$$

Where x is the actual value, x_{max} is the maximum value, x_{min} is the min value of x and Y is the normalized value corresponding to x.

The monitoring of the testing error is done while training progresses. The training and testing error normally decreases during the initial stages of training but the testing error increases slowly when the network begins to over fit the data. The training is stopped when the testing error increases for the specified number of iterations and the weights at the minimum value of the testing error are returned. The testing data is then provided to the trained network to check the variation of predicted output from the actual one.

In the present work, the number of input to the network is three (drill diameter, feed rate and spindle speed) and output is one (temperature). Best network architecture (number of neurons in the hidden layer, learning rate (η) and momentum coefficient (α)) is obtained by trial and error based on the convergence of mean square error (MSE) and the number of iterations. First, the optimum number of neurons for the hidden layer is found out at learning rate (η) 0.3 and momentum coefficient (α) 0.2. The architecture 3-5-1 gives the minimum MSE and is considered best for our case (shown in the figure 3). The network 3-5-1 was then trained and tested for various values of momentum coefficient (α) and learning rate (η). The optimal network is 3-5-1 with momentum coefficient (α) 0.2 and learning rate (η) of 0.5 (shown in Table 4). Although the MSE for the network design 3-5-1 with momentum coefficient (α) 0.2 and learning rate (η) 0.3 is minimum but for the design considered, the number of iterations reduces to almost half without any appreciable difference in the MSE. For applications with high accuracy requirements architecture 1 (shown in Table 4) can be adopted. Figure 4 shows the mean square error for training and testing of the data for the neural network (3-5-1, α=0.2, η=0.5). The comparison between the experimental values and results obtained by BPNN is shown in the figure 5. From the figure 5, it can be observed that the predicted temperature is within $\pm$ 10 percent of the experimental value. The Present study clearly shows that the BPNN model can be trained to predict the temperature during orthopaedic drilling with reasonable accuracy.

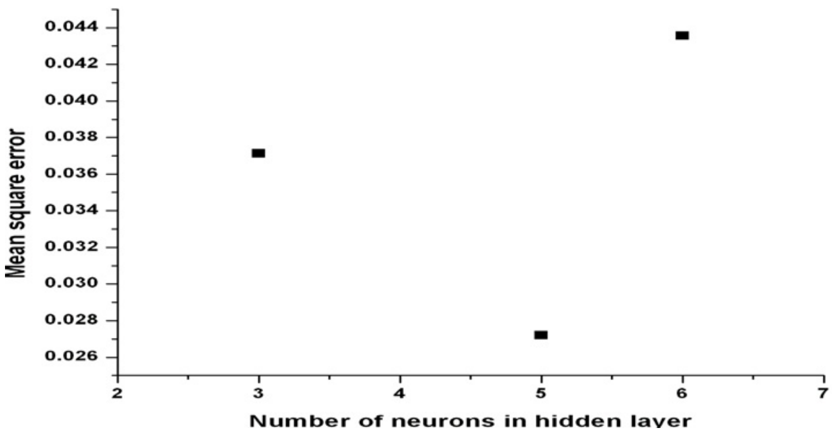

Fig. 3. Variation of mean square error with number of neurons in hidden layer

Table 4. Different BPNN structures used for predicting temperature during drilling of PMMA.

S.No	Network architecture	Momentum Coefficient (α)	Learning Rate (η)	Number of Interations	Mean square error training	Mean square error testing	Maximum predicted error (%)
1	3-5-1	0.2	0.3	410584	.0004485363	.0271964014	9.549698
2	**3-5-1**	**0.2**	**0.5**	**244800**	**.0004485164**	**.0275523149**	**9.613210**
3	3-5-1	0.5	0.3	252947	.0004484832	.0280403006	9.698814

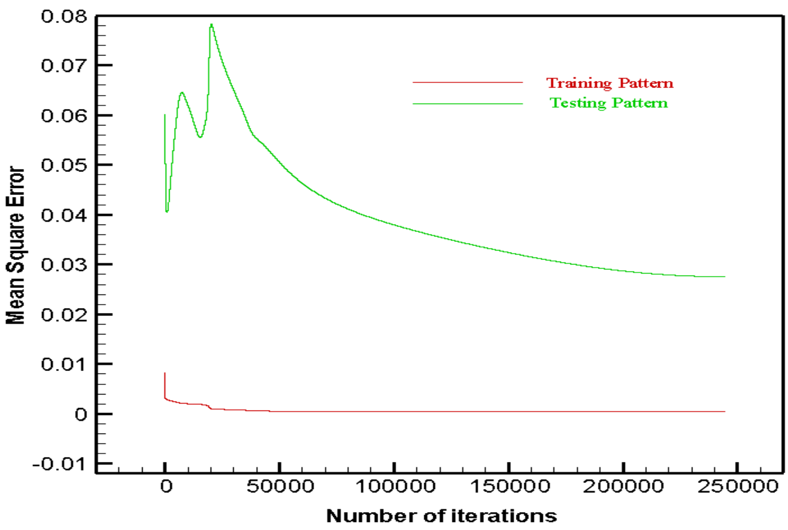

Fig. 4. Convergence of mean square error with number of iterations

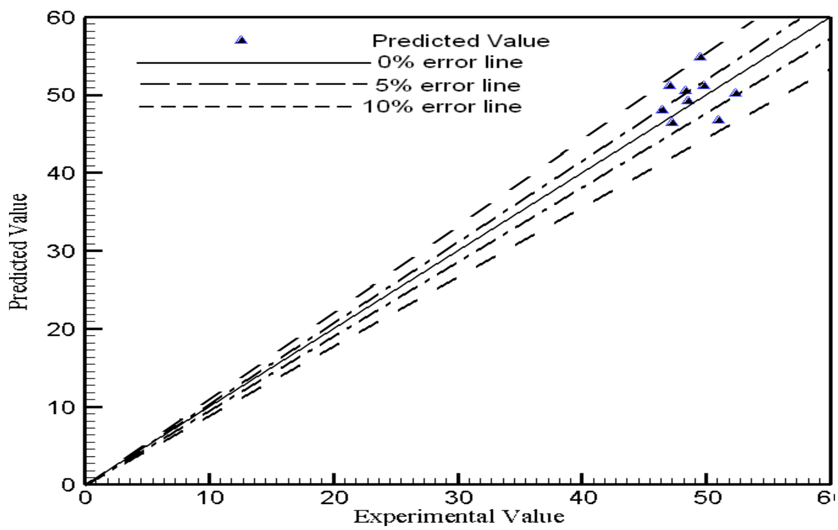

Fig. 5. Convergence of mean square error with number of iterations

5. Conclusions

Experiments are conducted on PMMA for analyzing the temperature produced in orthopaedic drilling. The machining parameters considered for the experiments are drill diameter, feed rate and spindle speed. From the above analysis, the following conclusions are drawn:

1. L_{27} orthogonal array of design of experiments (DOE) is selected for conducting experiments to take into account of the interaction affect on response in the design of BPNN model
2. Network with 5 neurons in the hidden layer is found to be optimal. Increasing the neurons beyond it increases the complexity of the system as indicated with increase in MSE.
3. The experimental results and the values predicted by BPNN model is fairly close (within $\pm$ 10 percent) which shows that the temperature during orthopaedic drilling can be efficaciously modeled using BPNN.
4. The developed system will simplify the tedious task of modeling and analysis of the temperature during orthopaedic drilling. The use of the above suggested system will reduce the risk of thermal osteonecrosis and can be very useful for the online monitoring of the process.

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